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Research on the application of computer science in wind power generation and the future trends

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Abstract. In the context of the growing global demand for clean energy, wind power, as an important form of renewable energy, is gradually occupying a dominant position. At the same time, the continuous development of computer technology has also brought new breakthroughs in wind power generation. Traditional wind power generation suffers from low power generation efficiency and large fluctuations in power generation. However, through the integration of wind power generation with advanced computer technologies, the efficiency and cost of wind power generation have been greatly optimized. This paper seeks to provide an overview of how computer science is utilized in wind power generation, focusing on the integration of computational modeling, simulation, and machine learning. It highlights future trendsand emphasizes the significance of developing digital twins and integrating machine learning with physical models for efficient wind farm management. Combining findings from various existing studies, this paper delves into the profound implications for the future of energy, highlighting the transformative role of computer science in advancing sustainable power solutions and shaping the landscape of renewable energy sources.

Keywords: Wind power, simulation, computer science, machine learning

1. Introduction

With the continuous advancement of global energy transition and carbon neutrality work, the global power system is decarbonizing, led by the increasing dominance of wind and solar energy [1]. Since ancient times, people have been able to use wind energy to promote production. In modern times, wind energy has gradually become one of the main primary energy sources for renewable energy generation. It is expected that, by 2050, the annual wind power generation will reach at least 20,000 TWh [1]. However, due to the natural volatility and temporal and spatial instability of wind energy, the low utilization rate of wind energy and the unstable impact on the power grid hinder the development of wind power generation. But with the development of computer science in recent decades, many computer technologies have been successfully applied to wind power generation, greatly reducing the potential impact of wind energy on the power grid and improving the efficiency of wind energy utilization. This paper focuses on summarizing the applications of computer modeling and simulation, machine learning, and neural networks in wind power generation. Meanwhile, it analyzes and summarizes the shortcomings and prospects of existing research on how computer science can be better

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applied in the field of wind power generation in the future, so as to approach the goal of carbon neutrality in human society by the middle of this century.

2. Computational Modeling in Wind Power Generation

2.1. Computational Modeling for Wind Turbine Design

There are mainly two types of wind turbines in the world today: vertical and horizontal, and the horizontal three blade structure wind turbine (HAWT) accounts for the vast majority of them [2]. Due to the fact that its three blades rotate around the central axis, the line velocity at the point further away from the axis of rotation on the blades increases while the angular velocity remains constant. This results in different relative speeds of the blades at different radii for the same wind speed. Therefore, the blade geometry of wind turbines should be different at different radii. In the past, a blade with high wind energy utilization could only be obtained through more complex calculations. With the maturity of computer modeling technology, the blade design work of wind turbines can now be completed on computers. At the same time, computer simulation technology can be used for verification and model optimization, in order to maximize the wind energy capture rate of wind turbines.

In the design process of wind turbine blades, the material of the blades plays a crucial role. Its physical and chemical properties, such as strength, quality, and corrosion resistance, will affect the lifespan and power generation efficiency of wind turbines. By using computers for modeling and simulation, existing digital models of different materials can be used to simulate various blade designs in real-life situations, thereby reducing waste of real materials and finding the most suitable blade materials and designs. This design process not only reduces the production cost of wind turbine blades, but also greatly improves design efficiency and blade usage effectiveness. Appadurai et al. used finite element analysis to design wind turbine blades using carbon epoxy values, graphite epoxy resin, and steel materials for stress simulation [3]. After a comprehensive analysis of quality and blade strength, they ultimately found that carbon epoxy composite material is the most suitable material for manufacturing wind turbine blades.

Computer modeling and simulation can also be applied to the study of load and dynamic characteristics of propeller blades. Numerical simulation can be used to analyze the performance of wind turbines under different environmental factors, such as wind speed, force conditions of propeller blades, vibration response, etc. This kind of simulation modeling can optimize the design, improve the efficiency and stability of wind turbines. Jucuan Dai et al. established a real-time dynamic simulation model of wind turbine blade load in the Simulink environment, and ultimately found that the flap torque is mainly affected by aerodynamic torque, with gravity having a greater impact on the edgewise torque of wind turbine blades [4].

2.2. Macro Simulation and Digital Twin in Wind Farm

In addition to modeling and simulation of wind turbine blades, at the macro scale, modeling and simulation of the entire wind farm also have a high guiding role in optimizing the establishment of wind farm structure and improving wind energy utilization efficiency. The power generation of wind farms largely depends on their layout, scale, and degree of direct matching with the power grid. Due to differences in wind direction and speed at different locations within the same power plant, wind farms often experience power fluctuations. Without appropriate reactive power compensation equipment, voltage fluctuations in wind farms can be quite significant [5]. Establishing a computer model during the construction and research of wind farms can help simulate major issues such as power generation, operation status, and system response. This allows for a quantitative description of power fluctuations in wind farms from the beginning and optimization of power fluctuations through simulation. It can also provide a solution for selecting the site of each unit during wind farm construction. The model used to describe the wake of wind power generation has been developing since the 1980s [6].

Nowadays, various fluid dynamics models can run well on computers and produce conclusions for optimizing wind farms. People have found that computer simulation has a natural and significant

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advantage in evaluating the macro level effects of the wake effect and other interactions between wind turbines in wind farms. Through computer models, simulation can be used to coordinate the direction, distance, and position of wind turbines, in order to reduce the impact of wake effects on wind power efficiency and maximize the utilization of local wind potential. Just like F Gonz á lez Longatt et al. used MATLAB to establish a wake model for wind power generation, and analyzed in detail the influence of wake effects on steady-state and dynamic behavior by changing factors such as wind direction, wind speed, and distance between generator units [7]. In the case where all details of the wind farm are unknown, the team's conclusion can serve as an empirical rule for general evaluation.

The current digital models for wind farms are mainly divided into three types: low-fidelity, medium-fidelity, and high-fidelity wind farm models [8]. Among them, the low-fidelity model is often a static model used to reflect the state of a wind power average state; the medium-fidelity model is already a dynamic model that can reflect more flow field characteristics and details but often uses simplified physical equations; and the high-fidelity model provides a high-precision wind farm model at the cost of computational complexity.

With the continuous development of computer technology, the computing power of computer CPUs and GPUs has increased exponentially. A real-time digital model that reflects the real situation of things has emerged in people's vision, which is the digital twin model. In the field of wind power, digital twins can also provide solutions for wind farm monitoring, control, and optimization. Due to the fact that the physical quantities established through simulation in the digital twin model can correspond one-to-one with the various physical quantities of the real world wind power field, it can achieve the control and optimization goals of the generator unit entity through real-time feedback and model interaction. The future application of computer simulation and modeling in wind farms should pay more attention to the real-time and punctuality of physical models. However, at the same time, we must also see the real physical situation, such as the impact of complex fluid dynamics, which brings challenges to the establishment of high-fidelity real-time digital twin models for wind farms.

3. Application of Machine Learning in Wind Power

3.1. Overview

Machine learning is a technology in the field of artificial intelligence. With the release of artificial intelligence models such as ChatGPT in recent years, the application of artificial intelligence in industries, medicine, and other fields has gradually been accepted by the public. Establishing a digital twin model for an industrial system can monitor and control the entire system in real-time, but the patterns or patterns of certain physical characteristics of the entire system still cannot be well grasped by people, resulting in cost waste or low production efficiency. Machine learning technology, on the other hand, can provide effective solutions for such problems. By learning and training from industrial system data, it can grasp the patterns of the data and make predictions or decisions. In the field of energy, the characteristics of machine learning can be well adapted to multiple factors in wind power generation. Wind power is greatly influenced by natural factors, and both wind speed and direction will affect the power generation of wind turbines. Therefore, machine learning the laws of local environmental wind will help to quickly and accurately adjust the orientation and blade angle of wind turbines, and improve wind energy utilization. At the same time, the power fluctuations generated by wind farms will also exert significant pressure on the power grid. The use of machine learning technology to predict wind power can also provide early warning and decision support for peak shaving of the power grid. The application of machine learning technology in wind power mainly revolves around the two aspects mentioned above. This paper elaborates on the application of machine learning technology in environmental factors and power generation.

3.2. Machine Learning in Wind Forecasting

When machine learning technology was not yet mature, weather forecasting was the main source of information for wind farms to predict wind energy for the next few days or months. However, weather

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forecasting often involves macroscopic predictions of a larger area, while it is difficult to achieve accurate predictions of more microscopic physical characteristics such as wind speed and direction in the local wind farm. Machine learning technology can generate learning models based on on-site monitoring data from wind farms over the past few years, allowing for more accurate predictions of future wind speeds and directions at the micro level. On a time scale, current environmental wind forecasting is mainly divided into four types: very short term, short term, medium term, and long term [9]. Machine learning technology is mainly applied in short-term and medium-term forecasting. Very short term prediction focuses on predictions ranging from a few seconds to a minute, mainly predicting wind speeds affected by turbulence and local meteorological conditions, while short-term and medium-term predictions are influenced by variations in thermal properties between the atmosphere and the ground, as well as changes in local weather patterns.

After decades of development, today's machine learning has incorporated artificial neural networks (ANNs) and may also couple with other mathematical and physical models to improve the accuracy of wind speed prediction. In [10], Chang et al. used multiple different neural network-based models, IRBFFNN-EF, for short-term wind speed prediction and proposed a new prediction method with error feedback, proving that the model helps to maximize wind energy capture. And M.M. Ardehali et al. integrated the artificial neural network with Markov Chain and used it for short-term wind speed prediction, while the Mc method was used for mid-term wind speed pattern analysis and prediction [11]. Also, LSTM(long short-term memory neural network), SVRM, and EO three computer-based algorithms were coupled by the investigators [12]. The resulting EnsemLSTM model can provide more accurate wind speed forecasting. Therefore, from existing research, coupling with mathematical or physical models can enable machine learning models to have higher prediction accuracy or time span, thus enabling better application in wind power prediction. However, traditional machine learning models based solely on neural networks are constantly being eliminated and banned. In future research, more attention should be paid to the integration of major data and artificial intelligence, as well as the integration of artificial intelligence and physical models in the real world, in order to make new energy generation more stable and predictable.

3.3. Machine Learning in Wind Power Prediction

The power of wind power generation fluctuates due to fluctuations in wind energy, and today, AC power grids around the world operate at a fixed frequency. This type of power grid requires each power generation equipment connected to the grid to have a fixed phase. Therefore, it is necessary to equip rectification and power stabilization facilities at the wind power generation end to reduce the impact of wind power instability on the power grid. At this point, predicting wind power will have multiple benefits for the operation of the wind power system. Firstly, it can actively improve the stability and reliability of the power grid, enabling the power system to better cope with fluctuations and changes and reducing the supply-demand imbalance caused by an unstable power supply. Secondly, predicting wind power can help optimize the operation and scheduling of the power system, improve power generation efficiency, and reduce energy production costs. Meanwhile, accurate power prediction helps power companies better plan future electricity demand and corresponding investments, promoting the sustainable development of renewable energy. Similar to wind prediction, machine learning a dataset of the power generation of a wind farm over a period of time can enable computer models to predict power levels for a future period of time based on existing data. Many machine learning algorithms used for environmental wind prediction can also be applied to wind power prediction.

Sina Ibne Ahmed er al. used two machine learning algorithms, Gradient Boosting Machine (GBM) and Support Vector Machine (SVM) to predict the medium- and long-term wind power generation, and they will incorporate neural networks in future work to better handle the randomness of data [13]. Researchers have also proposed a novel hybrid data driven model based on the concepts of deep learning-based convolutional-long short term memory (CLSTM), mutual information, evolutionary algorithm, neural architectural search procedure, and ensemble-based deep reinforcement learning (RL) strategies [14]. Compared with various advanced wind power prediction models in the world at that time, this prediction algorithm has excellent performance. It can be seen that constantly updated neural networks and machine learning algorithms will be closely related to wind power generation in the future. For the entire wind power system, wind power prediction should be combined with digital twin systems in the future, so that wind power utilization can be accurately controlled from the generation end to the grid end.

4. Conclusion

This paper mainly discusses the modern utilization of computer modeling and simulation, machine learning in wind power. These methods of utilizing computer technology greatly increase the power generation efficiency of individual wind turbines and wind farms, and reduce the volatility and predictability of their power generation. With the continuous development of emerging computer technologies such as artificial intelligence in recent years, the impact of wind power instability on the power grid will be further reduced, thereby accelerating the transition from traditional energy to renewable energy. In the future, in terms of computer modeling and simulation, wind farm models should develop towards high-fidelity real-time and data-driven digital twin models so as to make the control of wind power systems more precise and efficient. And wind power prediction should not be confined to the traditional neural network prediction mode, but introduce physical and mathematical models into machine learning, allowing computers to achieve higher prediction accuracy under supervised learning. Meanwhile, the above two technologies should be integrated and used to achieve higher system control efficiency and accuracy. Due to the limitations of computer models and the complexity of the real physical world, the challenges for the future application of computer technology in wind power generation will lie in the development of these two aspects.

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